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Exploring home-based reminder systems for daily routine support: usability, data insights, and future directions

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Abstract

Background: This study evaluates 'Remindful,' a home-based reminder system designed to support people living with dementia (PLwDs) and their caregivers, assessing its usability and the effectiveness of its integration into daily routines.
Research Aim: The study aims to refine and evaluate the usability of the 'Remindful' system, collect and analyze interaction data to optimize its functionality, and provide actionable insights that can inform the development of future digital reminder systems. The objectives focus on assessing the usability of the Remindful system to meet the practical needs of PLwDs and caregivers, demonstrating the feasibility of using collected data to optimize reminder delivery and identify usage patterns, and utilizing the findings to enhance future digital reminder systems by focusing on optimizing reminder timing and detecting anomalies.
Methods: Data were collected by logging reminder interactions from two dyads of PLwDs and caregivers to assess system usability in real-world settings. Data-driven techniques, including predictive modeling and anomaly detection, were applied to explore opportunities for optimizing reminder timing and identifying unusual usage patterns.
Results: The study analyzed the system's ease of use, user satisfaction, and the effectiveness of reminder acknowledgment across various home locations. The findings suggest that Remindful is effective in improving daily task management, though challenges in accessibility and reminder customization were identified.
Conclusion: The results emphasize the need for continuous user feedback in refining cognitive support technologies (CSTs) and demonstrate the system's potential in everyday settings. Future research should focus on broader testing to ensure adaptability and effectiveness across diverse populations.

Keywords: dementia, reminder systems, memory aids, assistive technologies, cognitive support technologies

Introduction

As global populations age, the prevalence of dementia is increasing, with estimates indicating that 5% of adults over the age of 65 are affected, a rate that doubles every five years (Pappadà et al., 2021). Dementia, marked by progressive cognitive decline, imposes significant emotional, physical, and financial challenges on individuals, caregivers, and society (Duong et al., 2017; Hubbard et al., 2003). This growing demographic demonstrates the urgent need for innovative solutions to support people living with dementia (PLwDs) in maintaining quality of life. Cognitive Support Technologies (CSTs)—a broad category of tools designed to assist with thinking-based tasks such as memory recall, decision-making, attention, and task management—include a variety of technologies such as memory aids and reminder systems (Astell et al., 2018; Mihailidis et al., 2008; Newton et al., 2016).

This research specifically focuses on digital reminder systems, a critical subset of CSTs. While CSTs in general offer important support, digital reminder systems have the unique potential to address the complex and evolving needs of PLwDs by providing real-time, personalized assistance with daily tasks. By improving the design and functionality of digital reminder systems, this study aims to better meet the individualized needs of PLwDs and their caregivers, enhance their autonomy, and reduce caregiver stress by streamlining task management. Thus, while CSTs are valuable, this research emphasizes the significant role that digital reminder systems can play in improving the quality of care and interaction between caregivers and PLwDs (Jönsson et al., 2019). In addition to usability, this study presents an early-stage analysis of reminder interaction data using statistical methods and machine learning to explore behavioral patterns and inform system optimization.

Background

Traditional memory-related CSTs, such as clocks, calendars, electronic timers, noticeboards, and pill dispensers, have long been used to help PLwDs manage daily tasks (King & Dwan, 2019). Although these tools are useful, they often are unable to manage more complex and individualized needs of PLwDs. To overcome these limitations, advanced CSTs, like digital reminder systems, have been developed to offer more dynamic and personalized support for PLwDs.

For example, the eSticky project integrated multiple reminders into a single system tailored for PLwDs (Mettouris et al., 2023). Moreover, the iRemember® system used Android tablets to provide auditory and visual cues for meals, and the MemBo Noticeboard served as a digital platform to help caregivers coordinate and share care information effectively (Jönsson et al., 2019; "Membo Noticeboard," 2024). The SALIG++ project also introduced an electronic memory aid featuring voice reminders and calendar systems to assist with appointments and medication management (Boman et al., 2016).

Despite these advancements, digital reminder systems still have limitations. They often fail to meet individual needs due to design flaws or an inability to adapt to the varying stages of dementia (King & Dwan, 2019; Sriram et al., 2020). Many systems are overly complex, which can overwhelm PLwDs rather than assist them, creating a gap between the functionalities offered and the actual needs of users. There is an evident need for more intuitive, accessible systems, highlighting the importance of user-centered design (UCD) to align with real-world needs.

In addition, the potential of reminder data remains underexplored. Data from system interactions could be leveraged to detect anomalies in user behavior, such as missed tasks or unusual activity, which may indicate cognitive decline. Optimizing reminder timing based on this data could also improve system effectiveness by delivering prompts when PLwDs are most receptive (Fikry & Inoue, 2023; Ho et al., 2020; Wang et al., 2021). These opportunities for data-driven improvements offer a promising direction for enhancing the effectiveness of digital reminder systems.

Objectives

This study aims to advance digital reminder systems, a subset of CSTs, through the development of 'Remindful', a home-based system for PLwD and their caregivers. The system utilizes the Internet of Things (IoT) for real-time communication and was built based on feedback from PLwDs and caregivers to ensure a user-centered design. The primary objectives are:

1. Evaluate usability: Assess the usability of the Remindful system, ensuring it meets the practical needs of PLwDs and caregivers through a user-centered approach.

2. Data collection and analysis: The system collects and analyzes reminder data to demonstrate the feasibility of extracting meaningful insights, such as optimizing reminder delivery and identifying usage patterns.

3. Provide insights for future CSTs: Explore how reminder data can improve future digital reminder systems, focusing on optimizing reminder timing and detecting anomalies to enhance dementia care.

Methods

This section outlines the methodologies employed in the development and evaluation of the home-based reminder system, Remindful, developed as a mobile application for PLwDs and their caregivers. It outlines the design process from initial concept and requirements gathering, through prototyping and user-centered design, to usability testing conducted in real-world settings. Further, it explains the data collection approach used to gather both quantitative and qualitative insights, including exploring whether it is possible to use the reminder data to optimize reminder times and detect unusual interactions that could indicate changes in user behavior or cognitive patterns. Each phase of the methodological approach is designed to refine Remindful's functionalities and enhance its usability, aligning closely with the needs and preferences of its end-users.

Mobile application development

The initial development of the Remindful app involved gathering user requirements, prototyping, and integrating essential features based on feedback from PLwDs and their caregivers (Sanchez et al., 2024). While the development process itself is not the focus of this study, this context is provided to support the understanding of the system's foundation and its evaluation in subsequent sections.

Initial concept and requirements gathering

The development of Remindful began with a comprehensive needs assessment to identify the specific challenges faced by PLwD and their caregivers. This involved a literature review to explore existing cognitive support technologies and traditional memory aids, followed by interviews with seven dyads of PLwDs and their caregivers. These interviews aimed to uncover challenges with managing tasks and reminders, and to identify gaps in existing solutions. Insights gained from the interviews informed the design and development of Remindful (Sanchez et al., 2024). For example, caregivers highlighted the need for a system that could support daily task management, while PLwDs expressed a desire for clear, simple reminders that would enable them to maintain independence without overwhelming complexity (Sanchez et al., 2024).

Design process

Remindful was developed using a UCD approach, actively involving PLwDs and their caregivers throughout (Sanchez et al., 2024). Their feedback was continuously integrated to shape the app's functionalities and user interface, ensuring it met the diverse needs of its users. The design process was highly iterative, starting with initial wireframes and evolving through multiple stages of mockups and prototypes. Remindful was designed to be installed on tablets referred to as 'reminder units,' strategically placed in various locations around the home. This setup allows caregivers or PLwDs to use a mobile device to deliver reminders to these reminder units, ensuring that assistance is readily available in the spaces where it's most needed.

Key features of the Remindful app include:

- Reminder creation and scheduling: The system enables caregivers to create, schedule, and deliver reminders for critical tasks such as medication, appointments, and personal care. Caregivers also have the flexibility to send reminders to specific rooms, such as scheduling mealtime reminders to be displayed in the kitchen. This room-based targeting enhances the contextual relevance of each reminder. Screenshots of Remindful's reminder creation and display interfaces are shown in *Figure 1*.

- Reminder delivery and acknowledgment: Once a reminder is delivered, users can acknowledge the reminder by tapping the screen, which in turn notifies caregivers that the reminder has been viewed, and the relevant task may have been completed. Additionally, scheduled reminders can be viewed on a calendar, as well as the frequency of acknowledged reminders.

- Integration with existing devices: As a mobile application, Remindful can be deployed on existing smart devices, such as tablets and mobile phones, to enable the delivery of reminders on familiar user interfaces. Additionally, it can connect with Google Home devices to audibly read reminders as calendar events.

- Customization options: The reminder system can be customized to accommodate different fonts, font sizes, images, and color schemes, based on the dyads' preference.

Usability testing

Usability testing was conducted in the homes of two dyads to assess the effectiveness of Remindful and gather valuable insights through real-world interactions with the system. Each dyad comprised family caregivers and PLwDs with mild dementia, as assessed by the Montreal Cognitive Assessment (MoCA), scoring between 18 and 25. Participants were recruited with the assistance of dementia research networks, ensuring a targeted and informed participant group.

Eligibility for the study required PLwDs to have received a dementia diagnosis within the last two years and to be able to speak and understand English fluently. They needed to understand and follow given instructions or prompts and provide informed consent. Caregivers had to be family or friends who provided care for at least 30 hours a week, spoke and understood English fluently, and were able to provide consent.

The first dyad involved a PLwD over 60 years old with mild cognitive impairment and a caregiver aged 51–60, in a husband-wife relationship, residing in a condo. The second dyad included a PLwD over 60 years old with Alzheimer's and a caregiver aged 41–50, in a mother-son relationship, living in a house. The caregiver in the first dyad had been providing care for less than one year, while the second had been caregiving for between one to five years. These dyads represent different caregiving dynamics (spousal vs. familial), home environments (condo vs. house), caregiver involvement (part-time vs. near full-time), and dementia severity. These contextual differences are important for interpreting usability outcomes, as they likely influenced how the system was used and experienced in each case.

The study specifically targeted family caregivers, who are the primary users of the home-based reminder system, aiming to enhance their communication and support in caregiving activities. The testing consisted of three main stages:

1. Initial setup: Three reminder units were installed in locations chosen by the participants, as shown in *Figure 2*. Remindful was also installed on the participants' phones to allow for the delivery of reminders from their mobile devices. A one-hour training session followed,

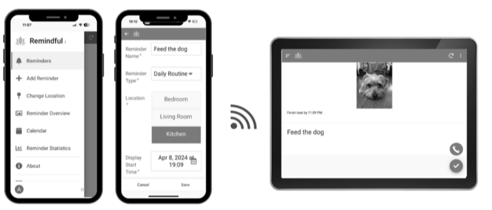

Figure 1. User interface of the Remindful app on mobile and tablet devices. The app's interface is displayed across a smartphone and a tablet, demonstrating the process of setting a reminder and delivering it to a reminder unit in the form of a tablet.

ensuring that participants could use the system to create, deliver, and acknowledge reminders. Participants were also provided with an instruction manual to support them during the testing period.

2. Testing period and data collection: During the testing period, participants were asked to deliver and acknowledge at least five reminders daily over the course of two to three weeks. These reminders focused on routine tasks, such as appointments and personal care, with instructions to avoid reminders related to medication intake or other tasks that could pose risks. The reminder interactions were logged in real-time and remotely accessed for data analysis.

3. Feedback session: At the end of the testing period, participants engaged in a feedback session, which involved a survey and a closing interview to gather qualitative insights on the system's usability and effectiveness. Feedback focused on system satisfaction, challenges encountered, and suggestions for improvements.

Tools and instruments

The following tools and instruments were employed during the usability testing to facilitate data collection and user feedback. These resources were essential in preparing for and capturing the interaction dynamics between PLwDs, their caregivers, and the Remindful system.

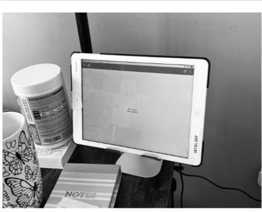

Figure 2a. The Remindful app displayed on a reminder unit.

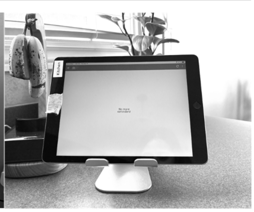

Figure 2b. The Remindful app displayed on a reminder unit in a kitchen.

Figure 2. Deployment of the Remindful app in different home environments.

1. Instruction manual:
A comprehensive manual was provided to guide caregivers through the app setup process and basic troubleshooting. This manual outlined key steps for installation and app usage, ensuring users could navigate the system with ease.

2. System logging and data collection:
Remindful automatically logged all interactions, capturing both the creation of reminders and the specific times and statuses of their acknowledgment. In addition, other data collected for each reminder included the location it was delivered to, whether a visual accompanied the reminder, whether it was set as a higher priority reminder, and the type of reminder it was. Types of reminders, inputted by caregivers during the reminder creation process, included appointment, personal hygiene, mealtime, daily routine, social engagement, exercise, and entertainment and hobbies. This data was stored and analyzed to assess Remindful's usage patterns and performance in helping PLwDs manage tasks independently.

3. Post-usability testing survey:
At the end of the testing period, both PLwDs and caregivers completed surveys to evaluate Remindful's ease of use, design, and overall functionality, with an overview of the questions and results shown in *Table 1*. They rated statements such as "It was easy for me to learn how to use the reminder system" and "The workflow of using the reminder system makes sense" on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). While standard usability instruments like the System Usability Scale (SUS) or NASA-TLX were considered, they were not used due to the exploratory and small-scale nature of the study. Instead, a custom survey was designed to provide targeted feedback on Remindful's specific functions and user interface elements, enabling a more focused evaluation aligned with the system's intended use by PLwDs and their caregivers.

4. Post-usability testing structured interview:
In addition to the surveys, interviews with dyads were audio-recorded, offering in-depth insights into their experiences with Remindful. Topics included navigation ease, reminder effectiveness, and technical challenges, with caregivers reflecting on Remindful's impact on their caregiving duties.

Data collection

This section outlines the methods used to collect both quantitative and qualitative data during usability testing. All data collected, including reminder interaction logs and qualitative feedback, were de-identified and securely stored on encrypted platforms. Access was restricted to the

Table 1. Post-Usability testing survey results from PLwDs and caregivers, where 1 = strongly disagree and 5 = strongly agree

	Dyad 1		Dyad 2	
Statement	**PLwD**	**Caregiver**	**PLwD**	**Caregiver**
1. It is easy to turn on the reminder units	1	5	2	1
2. The workflow of using the reminder system makes sense	2	5	4	3
3. It was easy for me to learn how to use the reminder system	3	5	1	5
4. I can deliver reminders easily	3	5	3	4
5. I can accept a reminder easily	3	2	5	4
6. The reminder units alerted me when a reminder was delivered	3	1	3	2
7. I can see when a reminder is accepted	3	3	5	2
8. The font size of the text is easy to see	2	5	5	5
9. I like the aesthetics of the reminder units (the mobile application)	3	5	5	4
10. I was able to interact smoothly with the reminder system to communicate with my caregiver/the person I care for	3	2	1	1
11. I see myself using a reminder system like the one I tested to assist me with my daily routines	3	3	3	1
12. I enjoyed testing the reminder system	3	3	4	4

research team, and all procedures followed institutional ethics protocols to ensure participant privacy and data protection.

Quantitative data

Through usability testing of Remindful, quantitative data was collected focusing on the type and frequency of reminders set and acknowledged, as well as the locations within the home where these interactions were most effective. Numerical scores to indicate participant satisfaction (i.e., on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree)) were also drawn from the post-usability testing survey.

Qualitative data

After the testing period, qualitative data was collected through structured interviews that gathered in-depth feedback about user experiences, challenges, and suggestions for improvement. Observational notes were taken by the researchers throughout the testing period to document any noticeable patterns or issues in how participants used Remindful. These qualitative methods provided a richer understanding of user interaction, beyond what could be measured through quantitative metrics alone.

Analytical methods for interaction data

This section details how data collected from the reminder system can be used to enhance dementia care, aligning with the objective to optimize reminder delivery and detect unusual usage patterns. It covers data preprocessing, optimization of reminder timings, and anomaly detection techniques.

Data preprocessing and augmentation

The reminder data collected from the Remindful app, which tracked interactions between PLwDs and their caregivers, was initially stored in raw form within a Google Sheet. This raw data, containing inconsistencies and non-numerical information, was not suitable for direct analysis. Therefore, a multi-stage preprocessing method was used to clean and structure the data for machine learning analysis, including tasks like standardizing dates and times and converting categorical data into a numerical format.

Data from the dyad with higher acknowledgment rates (Dyad 2) was used for further analysis, as their interactions more closely reflected realistic usage of the system. However, despite their higher engagement, this dyad provided a small dataset of 36 data points, which limited the model's ability to generalize. To address this, further data was simulated, increasing the dataset to 1,036 points, allowing for a more comprehensive evaluation of the model's performance across a broader range of conditions. This augmentation aimed to increase the dataset's variability and improve the robustness of machine learning models. While useful for initial model training, synthetic data carries inherent limitations, such as reduced unpredictability and potential biases introduced during generation. These factors were considered when interpreting results, and future studies should prioritize larger, real-world datasets for model validation.

Optimizing the timing of reminder deliveries

To demonstrate the possibility of improving the timing the reminders are displayed to PLwDs, a Random Forest machine learning technique was employed to analyze behavior and predict optimal display times. The analysis included factors such as acknowledgment times, reminder types, and delivery locations. The model was trained with 80% of the data and tested with the remaining 20% to validate accuracy. It then generated predictions on the best times to display reminders when the PLwD would be most likely to view and acknowledge them, and these predictions were recorded for further evaluation.

Identifying unusual interactions with the reminder system

Statistical and machine learning methods, including Z-scores and Isolation Forest models, were applied to detect unusual patterns in how individuals interact with the reminder system, also known as anomalies. These methods identified significant interactions, such as delayed or missed acknowledgments of reminders, which could indicate behavioral changes in PLwDs. Initially, acknowledgement times to reminders were measured using a Z-score analysis, where a threshold of ± 2 was set to identify outliers in the data collected from usability testing and flag any significant deviations for further review.

To deepen the analysis, an Isolation Forest model was employed, where multiple factors affecting user interactions were simultaneously considered, in addition to acknowledgement times. Specifically, the analysis included how the time of day and the location within the home where reminders were received might influence the likelihood of a reminder being acknowledged or missed. This comprehensive approach allowed for the detection of subtler shifts in behavior, such as changes in routine that occur at specific times or in specific areas of the home. Understanding these patterns enables caregivers to better recognize significant shifts in the routines of PLwDs that may suggest changes in activity.

Results

Results are presented from evaluating the reminder system, detailing user satisfaction, ease of use, and specific issues as reported by both caregivers and PLwDs. In addition, the system's strengths in organizing daily tasks, areas needing enhancement, and preliminary results on optimizing the timing of reminder deliveries and identifying unusual interactions with the system are demonstrated.

Usability testing – quantitative results

This section presents the quantitative results from the usability testing, detailing variations in reminder utilization, acknowledgment rates, location-based interactions, and survey insights to evaluate the effectiveness and user satisfaction of the reminder system.

Reminder frequency based on reminder types

Quantitative analysis revealed variations in the type and frequency of reminders used, with 'Daily Routine' reminders being the most frequently delivered and 'Social Engagement' the least. During the testing period, Dyad 1 engaged for three weeks and utilized a total of 72 reminders, while Dyad 2, which engaged for approximately two weeks, utilized a total of 36 reminders. This discrepancy in testing duration resulted in different levels of engagement between the dyads. Detailed statistics on the reminders created and delivered for each type, respective to each dyad, are shown in *Figure 3*.

Reminder acknowledgment

Acknowledgment rates varied significantly between dyads, as shown in *Figure 4*, with Dyad 1 showing a lower acknowledgment rate (35%) compared to Dyad 2 (89%). In this context, 'acknowledgment' involves users actively tapping a button to confirm that they have seen and responded to a reminder. This metric suggests variations in engagement and system usability, indicating the effectiveness of the reminder system in ensuring that reminders are not only delivered but also actively acknowledged and acted upon by the users.

Location analysis

As shown in *Figure 5a*, which illustrates the distribution of delivered reminders by location, and *Figure 5b* which illustrates the acknowledged reminders, there is a clear preference for the kitchen in both dyads. In Dyad 1, a substantial number of reminders were delivered to the kitchen, with a large proportion of these being acknowledged, as depicted in *Figure 5b*. The living room saw lower engagement, with a moderate number of reminders delivered, as shown in *Figure 5a*. The bedroom experienced the least interaction, with the fewest reminders delivered and acknowledged in both dyads.

Post-usability testing survey insights

Post-usability testing survey results revealed disparities in user satisfaction between caregivers and PLwDs, particularly regarding system usability and ease of learning, as evidenced by the responses to statement #3 in Table 1. Caregivers rated the system's ease of learning and use highly, with an average score of 5, indicating strong satisfaction. In contrast, PLwDs reported greater challenges, with a significantly lower average score of 2, demonstrating the need for more accessible interface designs to accommodate their specific requirements. Moreover, the surveys highlighted strengths in aesthetics and functionality but pointed out areas needing improvement, such as alert systems and communication features (*Table 1).*

Usability testing – qualitative results

This section explores the qualitative aspects of usability testing, exploring user satisfaction, ease of use, and identified challenges through detailed feedback from caregivers and PLwDs gathered during feedback sessions at the end of the testing period, as they interacted with the reminder system.

User satisfaction

Participants responded positively to the reminder system, particularly for its ability to help organize daily tasks and provide a clear visual structure for the day's schedule. Both caregivers and

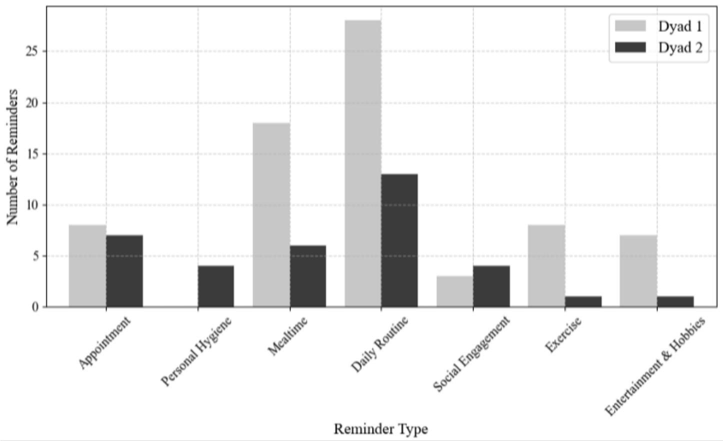

Figure 3. Distribution of reminder types by Dyad. Bar graph illustrating the number of reminders delivered for different types across two dyads.

es, suggesting the need for a more accessible interface for reminder display and acknowledgement. Despite these difficulties, the core function of delivering reminders was well-received, with both groups reporting they were able to use the system effectively once familiar with its basics. While acknowledgment rates served as a proxy for engagement, caregiver feedback also suggested that timely reminders contributed to improved task initiation and reduced repetitive prompting, indicating broader behavioral benefits.

PLwDs appreciated how the system supported maintaining control over daily routines. However, feedback indicated that while the system was valued, further refinements and additional features were needed to make it more practical for everyday use. Suggestions included adding customizable options to better match users' personal preferences. For example, some dyads expressed a preference for a to-do list format with multiple reminders lined up on the screen, rather than a display that only shows one reminder at a time. However, this approach may cause difficulty and potential cognitive overload for some users. This feedback presents an interesting contradiction to initial interviews described in Section 2.1, where dyads emphasized the need for clear and simple user interfaces, demonstrating the evolving perceptions of users as they interact with the system.

In terms of ease of use, caregivers found the system easier to navigate, especially when it came to inputting and managing reminders. While caregivers rated the system highly for usability and learning ease, PLwDs faced more challeng-

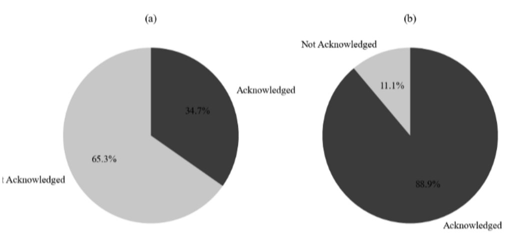

Figure 4. Acknowledgment rates for Reminder system in two Dyads. (a) Pie chart illustrating the acknowledgment rates for Dyad 1. (b) Pie chart showing the acknowledgment rates for Dyad 2.

Identified issues

Usability challenges were prominent during the testing phase. The most frequent concern raised by both caregivers and PLwDs was the complexity of entering and managing reminders. Participants felt the process was time-consuming and cumbersome. Another key issue was the visibility of reminders, as reminders would expire based on their scheduled times if not acknowledged, leading to confusion and missed tasks. Both dyads suggested persistent visual notifications or auditory alerts to prevent this problem. Additionally, participants expressed the need for a more streamlined process for entering recurring reminders, such as daily or weekly tasks, to reduce the cognitive load required for reminder input.

This feedback highlights the importance of refining the system's interface and features to enhance its usability and better meet the diverse needs of both caregivers and PLwDs. Additionally, the varied preferences expressed by different dyads highlight the necessity for a customizable approach, allowing the system to be tailored to the unique requirements and preferences of each pair, rather than adopting a one-size-fits-all strategy.

Results of interaction data analysis

This section presents the data analysis techniques applied to the data collection performed through usability testing, including machine learning models for optimizing reminder delivery, and anomaly detection to monitor unusual interactions between the PLwD and the reminder system.

Findings on optimal reminder timing

The Random Forest model demonstrated potential in identifying the best times of day—morn-

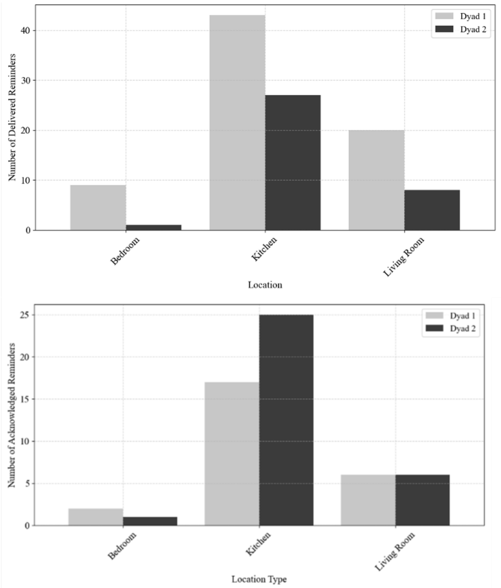

Figure 5. Distribution of delivered and acknowledged reminders by location in two Dyads. (a) Bar graph comparing the number of reminders delivered to three locations: the bedroom, kitchen, and living room. (b) Bar graph comparing the number of reminders acknowledged in three locations: the bedroom, kitchen, and living room.

ing, afternoon, or evening—for delivering reminders, with a moderate accuracy reflected by a mean squared error of 4.26 hours. This limitation is primarily due to the small volume of training data collected during usability testing. Despite the 4-hour difference between predicted and actual times, the model still serves as a promising starting point, particularly for identifying broader timeframes, such as morning or evening, rather than precise moments.

This level of accuracy could be useful for practical applications, like scheduling medication reminders in the morning when they were more frequently acknowledged, or setting personal hygiene reminders for the evening based on user interaction patterns. While the current error margin is relatively large, it still provides valuable insights for improving acknowledgment rates and tailoring reminders to the most effective time of day.

With more data—such as extended periods of app usage by more participants—the model's performance is expected to improve, enabling more accurate predictions of reminder timings. As the dataset grows and captures more user interactions over time, the model will become better at fine-tuning predictions and optimizing the effectiveness of reminders for each specific task and user. This proof of concept suggests that with further refinement and additional data, the system can significantly enhance dementia care through more personalized and effective reminder scheduling.

Findings on reminder use patterns

For the analysis of anomaly detection, usability testing data from Dyad 2 was primarily used, as they acknowledged significantly more reminders compared to Dyad 1. Anomaly detection initially employed Z-score analysis, which highlighted significant deviations in reminder durations and user interactions. This method identified outliers by measuring how far individual data points deviated from the average, using a threshold of ±2 standard deviations to classify anomalies. The Z-score analysis uncovered key insights, such as outliers in reminders for morning activities and those displayed in kitchen locations. Additionally, some negative duration outliers were detected, likely due to data entry or processing errors. This analysis also revealed variability in caregiver routines and how the timing of reminders impacted user interactions.

Building on the Z-score analysis, the Isolation Forest model was implemented to enhance anomaly detection by considering multiple features simultaneously, such as reminder duration, the timing of status changes, and the day of the week. This approach was more effective for handling complex data and detecting subtler patterns that the simpler Z-score analysis might miss. The Isolation Forest model successfully identified more intricate anomalies, highlighting interactions between different features. It also consistently detected similar outlier types across both the original and augmented datasets, validating the robustness of the method. Furthermore, the model demonstrated strong scalability, making it well-suited for larger datasets and real-time monitoring in dementia care settings.

Due to the absence of sufficient ground truth labels, formal metrics such as precision and recall for the anomaly detection models were not computed. This serves as an early proof of concept and future work will prioritize the inclusion of labeled validation data to enable more rigorous model evaluation using these metrics. Both the Z-score and Isolation Forest models served as strong proof-of-concept methods, demonstrating that it is feasible to perform anomaly detection using reminder data. These techniques offer promising initial steps in understanding and improving the timing and delivery of reminders, showing that reminder data can be leveraged to enhance support for individuals with dementia and their caregivers.

Discussion

This section discusses the key discoveries, limitations, and future insights from the study, focusing on enhancing dementia care through the targeted development and iterative improvement of our reminder system.

Reflection

Reflecting on the findings from the usability testing, the reminder system demonstrated substantial potential in enhancing the daily management of tasks for PLwDs and their caregivers. However, the variations in engagement and acknowledgment rates between the dyads demonstrate a critical need for adaptable interfaces that cater specifically to the user's capabilities and environments. For example, the higher engagement in kitchens suggests that the placement of reminders in frequent activity zones significantly heightens interaction. This insight can be communicated to caregivers prior to setting up the devices to help them maximize the effectiveness of the reminders. Additionally, caregivers can be informed that they can adjust the location of the reminder units if they find that the initial placements are not ideal for encouraging interaction and acknowledgment.

Survey results further emphasized the divide in usability perceptions between caregivers and PLwDs, highlighting the necessity for more intuitive designs that address the unique challenges faced by PLwDs. The feedback gathered suggests a pressing need for enhancing the system's alert mechanisms and communication features to ensure that reminders are both seen and acted upon effectively. It is also important to assess the needs of PLwDs separately from those of their caregivers, as their preferences may not always align. When gathering feedback, it is crucial to ask tailored questions for both parties, ensuring that the caregiver's preferences and the PLwD's preferences are considered independently, as these may differ in key areas such as interface simplicity, reminder timing, and interaction with the system.

Additionally, the study revealed a key distinction between allowing users to explore the prototype during design interviews under guidance and supervision versus having them navigate the system independently with support. Despite thorough setup instructions and guidance, users may still struggle to remember how the system works if it is not designed to be immediately obvious and intuitive. This suggests that for real-world use, particularly by PLwDs, the system must be straightforward enough to be easily recalled and used without continuous assistance. Moreover, participants' suggestions for a more streamlined process for entering multiple, recurring reminders demonstrate the cognitive load currently required by the system. A feature to simplify this process was intended to be included in the design, but could not be implemented due to technical limitations. Simplifying this aspect could lead to greater efficiency and reduce the potential for user frustration or errors, particularly for PLwDs who benefit from minimal cognitive strain.

Furthermore, the analysis of unusual interactions and the optimization of reminder timings through machine learning models lays a foundation for predictive adjustments that can further personalize the reminder experience. As more real-world data is collected over time, the performance of machine learning models, such as those used to optimize reminder timing and detect anomalies—can be substantially improved. Larger datasets will allow for better generalization, more accurate predictions, and personalized adjustments that reflect the evolving routines and needs of each PLwD. These technological advancements, while promising, will require continuous refinement and expansion of the training datasets to enhance their accuracy and reliability.

Key Discoveries

The findings from this research provide significant insights into the development and effectiveness of CSTs for PLwDs. The discoveries outlined below highlight aspects of the reminder system's impact, showcasing advancements in design, functionality, and user engagement that can be used to shape future developments in the field.
UCD and engagement: This study highlights the critical role of UCD in the development of cognitive support technologies. By involving PLwDs and their caregivers actively in the design process, the reminder system was tailored to meet the specific needs of its users, enhancing usability and satisfaction. That being said, there remains significant potential for further improvements, reinforcing that user involvement should be an iterative and ongoing process, not a one-time event. This participatory approach not only improved the functionality of the system but also empowered users, demonstrating the importance of user involvement in creating effective assistive technologies. Offering customizable reminder formats—such as lists versus single pop-ups—can further support personalization, ensuring the system accommodates a range of cognitive needs and user preferences.

Ease of use and automation in assistive technologies: A key discovery from this study is the importance of making CSTs intuitive and simple to support widespread adoption. The system should facilitate ease of setup and use, enhancing user accessibility. Specifically, simplifying the interface, particularly for PLwDs, is essential to reduce cognitive load and improve independent usability. Moreover, placing reminder units in high-traffic areas, such as kitchens, may increase the likelihood of reminders being seen and acknowledged, improving the system's effectiveness in supporting task initiation. Finally, by automating the scheduling of reminders, such as predicting optimal times for their delivery, CSTs can significantly streamline the effort required from users.

Data-driven optimization: Leveraging data-driven insights has been pivotal in optimizing the reminder system. The study demonstrates that data collected through the reminder system usage can facilitate data-driven optimization and monitoring, serving as a proof of concept for future work in developing more tailored and effective solutions. This study illustrates the value of incorporating advanced data analysis to enhance the adaptability and functionality of CSTs.

Comprehensive testing and diverse data needs: The findings show the need for more extensive testing and the acquisition of diverse datasets to ensure the robustness and generalizability of the technology. Testing should be expanded across various demographic and clinical groups to better adapt the technology to a broader range of user needs and environments. For example, testing with caregivers from diverse age groups can help assess the system's usability across different life experiences and familiarity with technology. This approach will ensure the system is intuitive and effective for all users, enhancing its applicability and support in varied caregiving settings. Future implementations should also explore persistent or repeating reminders to reduce the likelihood of missed tasks, particularly for users with fluctuating attention or memory retention.

Integration with emerging technologies: The study identifies the benefits of integrating the reminder system with other digital technologies, such as smart home devices. This integration could facilitate more seamless interactions and provide additional data points to further enhance the system's effectiveness. By leveraging these technologies, the reminder system can become more accessible and embedded within the user's everyday environment.

These key discoveries not only reflect the current insights from the study but also demonstrate the practical benefits and impactful possibilities of cognitive support technologies in real-world settings.

Limitations

This study encountered several limitations that may influence the interpretation and generalizability of its findings. Firstly, the sample size was limited and lacked diversity, as participants were primarily recruited from a specific geographic area and shared similar demographic characteristics. This homogeneity may restrict the ability to generalize the results to a broader population of PLwDs and their caregivers. Additionally, the usability testing was conducted predominantly in home environments, which introduced variability in testing conditions such as differing levels of caregiver involvement and environmental distractions. These in-home testing conditions could have affected the usability outcomes by introducing uncontrolled variables that might not be present in more standardized testing settings. This small-scale approach was intentional for establishing proof of concept within a constrained research timeline and to enable in-depth, iterative testing in real-world settings.

Furthermore, technical issues, including occasional bugs in the Remindful app and data collection inconsistencies, were encountered during the study. These technical challenges potentially impacted the reliability of the data and the performance of the machine learning models. The features and dataset size explored by the machine learning models were also limited, which may have constrained the scope of the analysis. The identified limitations, such as sample homogeneity, variable testing environments, and technical issues, could introduce bias and variability into the results. To mitigate these effects, the study employed data preprocessing techniques and robust machine learning methods, in addition to generating additional augmented data; however, some bias may remain.

Future insights

In discussing future research and insights related to the reminder system for dementia care, several important areas emerge for further exploration and development. Longitudinal studies should be conducted to evaluate the sustained impact of reminder systems on PLwDs and their caregivers over extended periods. These studies would provide insights into the long-term effectiveness of the system and how it can evolve with the progression of dementia. Additionally, personalization and adaptation should be key areas of focus. Future research can explore how the reminder system can dynamically adapt to the changing needs of PLwDs, including personalized features that cater to individual preferences and stages of cognitive decline.

Technological enhancements present another significant avenue for future research. Integrating the reminder system with other assistive technologies and IoT devices could create a comprehensive support network, offering a more holistic approach to dementia care. Moreover, leveraging advanced data analysis techniques like machine learning can further optimize the system's ability to predict and respond to the needs of users, enhancing the efficacy of reminders.

User feedback and involvement will remain central to continuous system improvement. Ongoing input from PLwDs and caregivers can guide future iterations of the system, ensuring that it remains user-friendly and effective. Embracing UCD by involving users directly in the development process will ensure that the system addresses real-world needs and challenges.

Lastly, it is crucial to address diversity, equity, and inclusion in future research. Ensuring that studies include participants from diverse backgrounds and contexts will make the system more universally applicable, while also addressing any disparities in access to cognitive support technologies.

Conclusion

This study has uncovered significant insights into how reminder systems can support PLwDs and their caregivers, emphasizing the importance of tailored interactions such as the timing of reminders. While the results demonstrate the potential of using statistical and machine learning methods to enhance care delivery, they also highlight the impact of technical issues and the limitations of the current feature set. Looking ahead, expanding the scope of machine learning features and addressing data reliability will be crucial in refining the effectiveness of these systems. Ultimately, this research prompts a broader consideration of how technology can be sensitively and effectively integrated into dementia care, ensuring that innovations not only address immediate needs but also enhance the overall quality of life for affected individuals and their caregivers.

Statement of ethics

This study protocol was reviewed and approved by the University of Toronto Research Ethics Board, approval number 00044727. Written consent was obtained from all participants prior to participating in this study.

Conflict of interest statement

The authors have no conflicts of interest to declare.

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Author contributions

AS (Co-Author): Developed the reminder system, facilitated all useability testing sessions, performed qualitative and quantitative data analyses, and translated data into meaningful results.

JL (Co-Author): Developed the reminder system, performed qualitative and quantitative data analyses, and translated data into meaningful results.

AT (Co-Author) - Facilitated useability testing sessions, performed qualitative and quantitative data analyses, and translated data into meaningful results.

AM (Co-Author): Led the direction of the research, provided expert guidance, and facilitated outreach efforts.

Data availability statement

The data for this study is not publicly available due to privacy and ethical considerations. Given the sensitive nature of the information gathered from participants, sharing the raw data could compromise the confidentiality and privacy of the individuals involved.

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